Adaptive Traffic Control Systems and Urban Traffic Congestion: Evidence from Los Angeles

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Abstract

Traffic congestion represents a ubiquitous and serious urban problem around the world. Policymakers frequently enact expensive policies like highway lane expansion, expansion of public transportation, and driving restrictions based on license plates to combat traffic congestion. Adaptive Traffic Control Systems (ATCS) that dynamically alter the red/green cycle timing based on real-time traffic conditions represent an increasingly popular, low-cost approach to reducing congestion. We analyze the impact of the installation of 4,700 ATCS signals in Los Angeles City in 2013 on local traffic congestion using the synthetic control method. Results based on panel data from 96 California cities over the period 2010-2017 show that the ATCS signals did not reduce congestion in Los Angeles, but they did slow the increase in congestion relative to the increase in the synthetic unit, suggesting that ATCS signals impact traffic congestion but cannot effectively reduce it.

JEL Codes: O18; R41; R53

Keywords: Adaptive Traffic Control Systems, traffic congestion, synthetic control

Introduction

Traffic congestion plagues cities around the world, generating serious negative economic impacts like reduced productivity and increased air pollution. A number of approaches for reducing urban traffic congestion exist, ranging from massive infrastructure investment into new roads or lanes and expansion of public transit, to draconian restrictions on driving based on license plate numbers. Cities increasingly employ congestion tolling, which, while effective requires large investment in monitoring equipment and involves undesirable distributional consequences [Hall, 2021].

Adaptive traffic control systems (ATCS, sometimes called adaptive traffic lights) represent one relatively inexpensive approach to potentially reduce urban traffic congestion. Most urban traffic light systems operate on fixed red/green cycles that vary by time of day and day of week. ATCS dynamically alters the red/green cycle timing based on current traffic conditions and is reflected in both data from induction loop sensors in roadbeds at intersections or crowd sourced data from popular driving apps like *Waze*. ATCS can be installed relatively quickly and cost effectively.

A number of studies analyzed the impact of driving restrictions, commonly based on the last number on license plates, find that these restrictions led to substantial improvements in air quality, but also led to

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offsetting behavior such as the purchase of additional vehicles which attenuated the impact on congestion [Carrillo et al., 2016, Hanna et al., 2017, Zhang et al., 2017]. Previous research reported tolling in central cities decreased congestion [Santos and Fraser, 2006, Gibson and Carnovale, 2015, Hall, 2021, Tang, 2021]. Most of the existing evidence of the impact of ATCS on traffic congestion comes from the traffic engineering literature and employs either simulations or case studies on individual intersections.

Sanchez et al. [2019], to our knowledge, the only paper in economics focused on ATCS, analyzed the impact of installation of a number of ACTS in Medellín, Columbia in a difference-in-difference framework using spatially and temporally disaggregated traffic speed and flow data from *Waze*. The results showed that installing six ATCS, each controlling several blocks of traffic lights, reduced congestion and increased speed in treated areas compared to areas without ATCS.

We exploit the installation of ATCS signals at more than 4,700 traffic lights in Los Angeles City in 2013 to assess the impact of these systems on urban mobility. Results from a synthetic control model indicate that the ATCS system in Los Angeles did not reduce traffic congestion in the City of Los Angeles. Traffic congestion in the treated city continued to grow following the installation of the ATCS signals. However, the increase in congestion in Los Angeles was significantly lower than in the synthetic unit, in some years as much as two hours of delay per resident per year, indicating that the signals had some impact on traffic congestion.

This paper contributes to the literature by analyzing ATCS signals as a method to reduce traffic congestion. Despite its increasing popularity, this policy has remained largely unexplored by the literature. It also contributes to the empirical literature confirming that the fundamental law of road congestion [Duranton and Turner, 2011] applies to situations beyond road expansion, including new road construction [He et al., 2019], expanding public transit [Gaduh et al., 2022], and license plate-based driving restrictions [Zhang et al., 2017]. The finding provides important information for transportation policy makers considering the installation of ATCS signals.

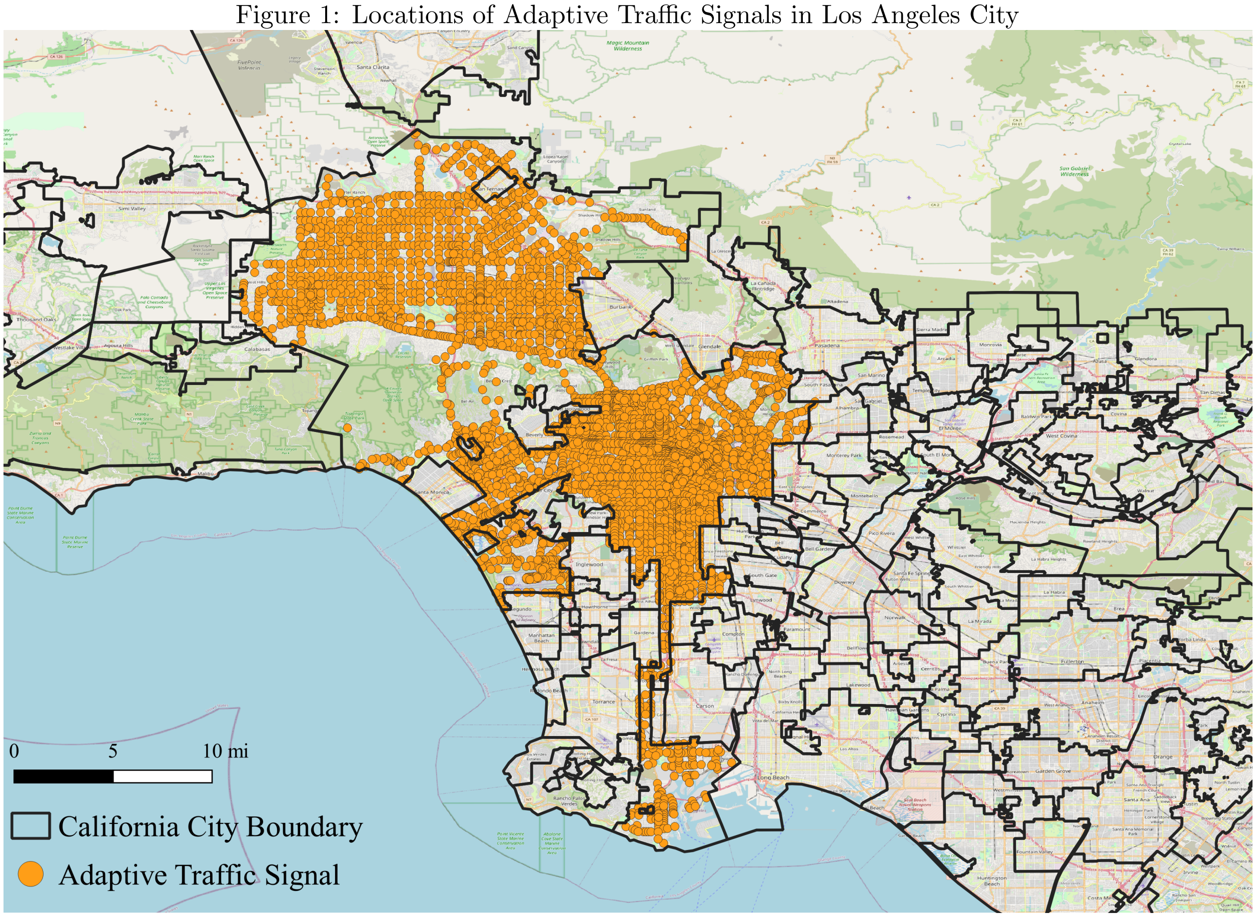
Data Description

We analyze data from cities in California. Duranton and Turner [2012] argued that cities represent the relevant unit of spatial analysis for research on traffic and congestion. We assemble an analysis data set at the city-year level from a variety of source, including the California Department of Transportation (Caltrans), the US Census Bureau, and the California Employment Development Department (EDD) over the period 2010-2017, three years before and four years after the ATCS installation in the City of Los Angeles. We match traffic data from Caltrans with sub-county population and labor market outcome data at the city level.

4,781 ATCS traffic lights were installed in Los Angeles County in 2013. 4,717 were located in the City of Los Angeles and the rest were spread around the county in unincorporated areas (36 traffic lights) and in nine other incorporated cities in Los Angeles County. Most of these cities installed only one ATCS traffic light. Data on the location of the ATCS intersections comes directly from the Los Angeles County Department of Transportation. Figure 1 shows the location of intersections with ATCS traffic signals.

Given the concentration of these traffic lights in the City of Los Angeles, we use the city as our treated spatial unit of observation and omit all other cities in Los Angeles County with ATCS traffic signals from the analysis sample. 10 other Cities in Los Angeles County got ATCS signals in 2013, but the small number of treated intersections in these cities, and the small size of some of these cities make them non-comparable

Figure 1: Locations of Adaptive Traffic Signals in Los Angeles City



Note: Orange dots show the location of adaptive traffic signals installed in Los Angeles City in 2013.

with the City of Los Angeles.

Traffic delay represents our outcome variable of interest. Data on traffic delay come from the Performance Measurement System (PeMS) maintained by Caltrans. PeMS collects and disseminates data collected from Vehicle Detector Sensors (VDS) location on roads in California. There are 18,660 VDSs in California, each reporting flow and occupancy data every 30 seconds [Caltrans, 2020].

The traffic data in PeMS come from VDSs located on principal arterial roads, which include Interstate Highways, US Routes, and State Routes in California. While Interstate Highways do not contain traffic lights, many principal arterial roads do. Also, many of the ATCS traffic lights are located at or near limited access highway on and off ramps. We assume that ATCS lights on non-interstate roads will also affect delay on interstates because principal arterial roads provide the main access to the limited access highway system.

PeMS contains variables that estimate traffic delay in terms of hours of delay at a specific threshold free-flow speed. The traffic delay measures reflect the additional time that a vehicle takes to traverse a road segment at the actual measured speed relative to how long it would take traveling at a benchmark free-flow speed [Caltrans, 2020].

For example, consider a vehicle travelling at the threshold speed of 35 mph over a 5 minute period. At the threshold speed, this vehicle would travel 2.91 miles. Suppose that traffic congestion limits the actual vehicle speed to 25 mph over the 5 minute period. Travelling at 25 mph, a vehicle takes 7 minutes to cover 2.91 miles, generating 2 minutes of delay relative to the free-flow speed of 35 mph. If 30 vehicles passed through this highway segment over this 5 minute period, the actual speed of 25 mph would generate an hour of vehicle delay relative to the free flow speed of 35 mph over this 5 minute period.

We use 35 mph as the benchmark free-flow speed for calculating traffic delay. The recorded speed and vehicle counts are used to estimate traffic delay over five minute periods. The PeMS interface allows for aggregating these estimates to specified spatial and temporal levels. In our case, we aggregate the traffic delay variable to the city-year level, matching the spatial and temporal unit of measurement for the other control variables.

Annual city-level population data come from the U.S. Census Bureau[1]. These annual sub-county population estimates reflect both census population counts and annual changes in housing units. Annual city-level labor market data come from the California Employment Development Department (EDD)[2]. The underlying source of these city level variables is the US Bureau of Labor Statistics Local Area Unemployment Statistics program. Note that all these variables ultimately come from the Current Population Survey, so the estimates reflect data based on place of residence, not place of employment. All vehicular travel originating at a residence or ending at a residence will reflect the counts in these data.

Travel to and from work represents a large portion of urban mobility. We collect data on annual total number of residents employed and total number of residents unemployed for a panel of 96 cities in California over the period 2010-2017. Combining these data with annual population estimates by city permits the calculation of the labor force participation rate, employment to population ratio, and the unemployment rate.

The treated spatial unit in this analysis, the City of Los Angeles, represents an outlier in terms of population and employment among the sample of California cities. The population of Los Angeles City, about 3.9 million residents, is more than double the population of the next largest city in the state, San Diego City, which averaged about 1.3 million residents over the sample period. The median annual population

[1] https://www.census.gov/data/datasets/time-series/demo/popest/2010s-total-cities-and-towns.html

[2] https://www.labormarketinfo.edd.ca.gov/data/interactive-labor-market-data-tools.html

Table 1: Summary Statistics - Delay and City Characteristics

	Mean	S.D.	Min.	Max.
Full Sample, N=768 city-years				
Annual Hours Delay at 35 mph	738,750	2,559,054	0	31,659,149
Annual Hours Delay per capita	2.88	2.84	0.00	18.46
Median Age	40.80	2.34	33.90	48.20
Median Earnings	38,745	12,084	22,229	80,518
% City Residents Female	45.79	1.97	40.50	49.51
% Residents working in city	78.40	15.68	38.85	98.11
Employment-Population Ratio	0.46	0.05	0.33	0.69

Note: Balanced panel of 96 California cities 2010-2017. Delay variables expressed as annual total vehicle hours delayed relative to 35 mph free flow speed.

across the cities in the sample is just 60,588 and the average is 107,000. In order to make outcomes across cities more comparable, we transformed the key outcome variable to per capita terms.

Table 1 shows summary statistics for the outcome and predictor variables for the full sample of 96 cities in California. Our main outcome variable, annual hours in traffic delay per city resident relative to 35 mph free-flow speed, is roughly 2.88 hours per resident. The largest value for the annual delay variable comes from Los Angeles, as expected. The maximum value for the annual delay per capita variable, about 18.5 hours per year, comes from Baldwin Park, a city of 70,000 in the San Gabriel valley region of Los Angeles County. The labor market and demographic predictor variables exhibit substantial variation.

Empirical Analysis

We use the synthetic control method [Abadie et al., 2010, Abadie, 2021] to analyze the impact of the introduction of automated traffic signals in the City of Los Angeles in 2013 on traffic congestion. Recent research in economics uses the synthetic control method to analyze traffic congestion. For example, Luechinger and Roth [2016] use synthetic control to analyze the impact of a truck mileage tax on traffic congestion in Switzerland. The synthetic control method creates an artificial counterfactual based on a weighted average of outcomes in untreated groups to compare to the outcome in a treatment group. The counterfactual control city matches changes in predictor variables in the pre-treatment period. The synthetic control method is ideal for this research question because there is only one treated unit - Los Angeles City.

In our case, 2010 to 2012 represents the pre-treatment period. The donor pool includes 96 cities in California that did not install ATCS with complete data for the 2010-2017 period, a balanced panel. We drop incorporated cities in Los Angeles County that got a handful of ATCS signals from the donor pool, as they were "partially" treated relative to Los Angeles City, which installed more than 4,700 ATCS signals in 2013.

Our predictor variables, the median city age, median city earnings, the fraction of the city population that is female, the fraction of the city population that works in the city, and the ratio of employed residents to the city population, reflect labor market outcomes and demographics. Since commuting to and from work constitutes a large fraction of vehicle travel in cities, variation in labor market outcomes and demographic factors related to labor market outcome should predict traffic delay. Note that we also include two lags of the outcome variable from the pre-treatment period in the the predictor variables.

Table 2 summarizes the predictor balance for our synthetic control model. From Table 2 we obtain good balance for all predictor variables. The average values of the predictor variables in the treated and synthetic control groups are very similar. When compared to the overall average in the sample, the treated and synthetic cities have a younger population, lower median earnings, and more residents working locally than the average across cities in the sample.

Table 2: Synthetic Control Predictor Balance

Variable	Treated	Synthetic	California Average
Median age in city	39.50	38.70	40.80
Median earnings in city	29,126	29,133	38,745
% residents working in city	96.47	93.42	78.40
% residents female	45.06	45.04	45.79
Employment-Population Ratio	0.45	0.45	0.46

Note: Table shows average value of predictor variables for Los Angeles City ("Treated") and synthetic Los Angeles City ("Synthetic"). The last column contains the average value for the entire 96-city sample shown in Table 1.

The left panel of Table 3 shows the six California cities that constitute synthetic Los Angeles city. These cities vary in population from 76,000 in Baldwin Park to 333,000 in Santa Ana. All six cities are in southern California. Three of the cities are located in Los Angeles County, two in Orange County, and one in San Diego County. Together, these six cities make up 99.9% of the synthetic Los Angeles.

Table 3: Estimated Synthetic Control Weights and Outcome Balance

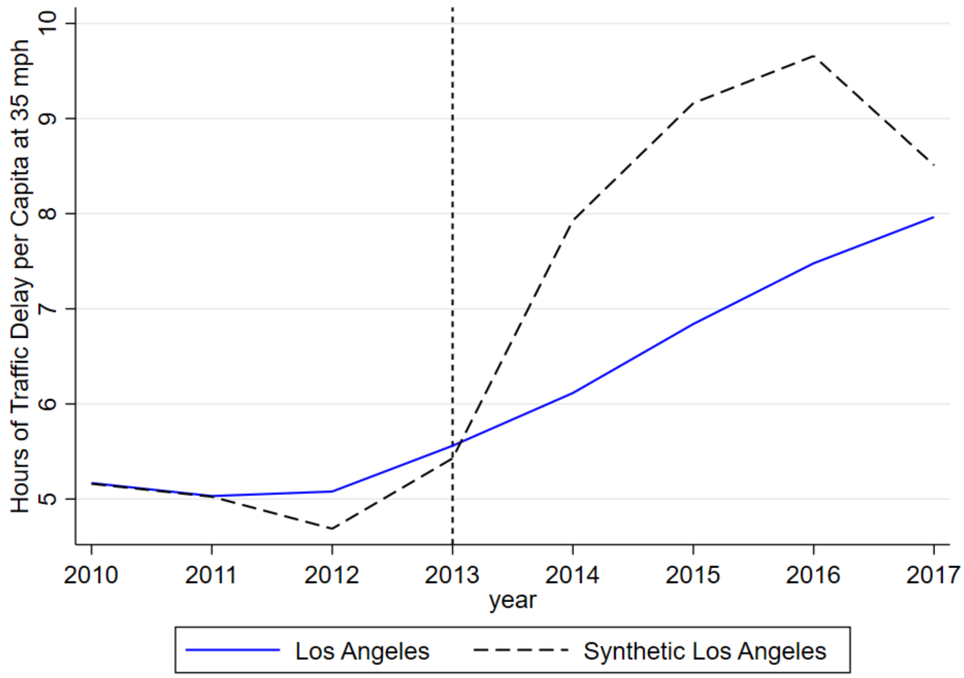
Estimated Weight	City	Year	Delay in Treated City	Delay in Synthetic City
		2010	5.17	5.16
0.390	Hawthorne	2011	5.03	5.02
0.210	Costa Mesa	2012	5.07	4.69
0.161	Baldwin Park	2013	5.56	5.43
0.082	Escondido	2014	6.11	7.92
0.082	Santa Ana	2015	6.84	9.16
0.074	Norwalk	2016	7.48	9.66
		2017	7.96	8.51

Note: The left panel shows the six cities that contributed the most to creating synthetic Los Angeles City and their estimated weights. Together, these cities make up 99.9% of the synthetic Los Angeles. The right panel shows the per capita annual hours of traffic delay at 35 mph for Los Angeles City ("Delay in Treated City") and the synthetic Los Angeles City ("Delay in Synthetic Unit") for each year in the sample. These values are visually displayed in Figure 2.

Figure 2 shows the main synthetic control results in graphical form where the treated unit, Los Angeles City, appears as a solid blue line and the synthetic control unit as a dashed line. Before the installation of the ATCS signals, both Los Angeles City and the synthetic Los Angeles were relatively similar in terms of their per capita hours of traffic delay at 35 mph. Traffic delay increased somewhat in the final pre-treatment period in both. This is visual confirmation of the match of synthetic Los Angeles's to the actual outcomes in Los Angeles City in the pre-treatment period. A strong pre-treatment match increases our confidence in post-treatment claims about the impact of ATCS signals on traffic delay.

From Figure 2, the installation of ATCS signals did not reduce traffic delay in Los Angeles. Traffic delay in Los Angeles grew steadily from about five hours per resident per year in 2012 to about eight hours per year in 2017. However, traffic delay in synthetic Los Angeles grew much faster over this period, from just under five hours per resident per year in 2012 to more than nine hours in 2016. The right panel on Table 3

Figure 2: Synthetic Control Estimation Results



Note: Figure illustrates the synthetic control estimation results. The blue line plots the per capita hours of traffic delay at 35 mph in Los Angeles City. The dashed line plots the synthetic Los Angeles City's traffic delay.

shows the outcome balance for each year in the sample, comparing the outcome in the treated unit to the outcome in the control unit. From Table 3, the difference in delay between Los Angeles and the synthetic unit was about two hours of delay per person per year at the peak between 2014 and 2016. The presence of ATCS signals in Los Angeles reduced the growth in traffic delay compared to synthetic Los Angeles, but did not eliminate increases in delay.

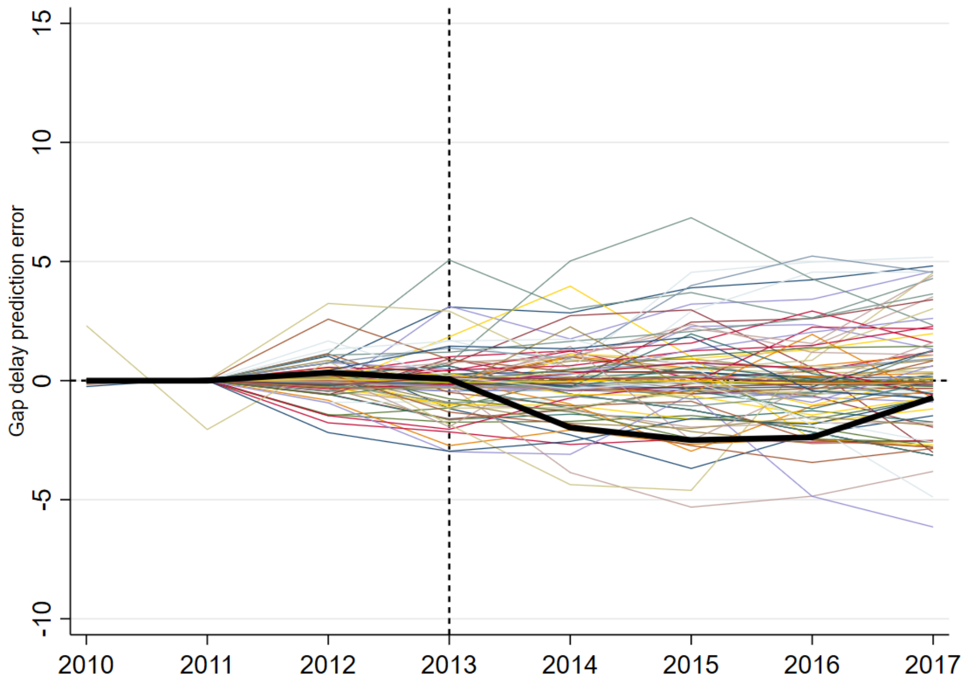
Traffic delay fell in the synthetic unit in 2017 but not in Los Angeles. This decline in traffic delay also occurred in the full sample of California cities, suggesting the presence of some negative shock to driving demand that did not affect residents of Los Angeles City. This widespread decline in delay reduced the gap between the treated and control units to less than one hour per person per year.

Figure 3 shows the standard randomization diagnostic for synthetic control models. Each line in Figure 3 systematically assigns the treatment to each city in the sample and uses all untreated cities as the donor pool. The lines show the gap between traffic delay in the cities randomly assigned as treated and the synthetic unit for that city expressed in difference in hours of delay at 35 mph. The thick black line shows the results for Los Angeles. The actual outcome lies in the tail of the distribution of the placebo outcomes. In other words the outcome in Los Angeles differs substantially from the placebo distribution for other cities in California.

Conclusions

We analyze the impact of the installation of 4,700 adaptive traffic control system signals in the City of Los Angeles on traffic delay using a synthetic control approach. Synthetic control applies to this case because

Figure 3: Difference in Actual and Placebo Distributions



Note: Figure shows the difference between actual hours of traffic delay in Los Angeles and the synthetic control groups generated when all other cities are defined as treated.

these ATCS signals were only installed in Los Angeles City. The results indicate that the signals did not reduce traffic delay in Los Angeles, but they did reduce the increase in traffic delay relative to the increase experienced in the synthetic unit in the post-treatment period.

The results provide mixed support for the effectiveness of ATCS systems to control traffic delay. As predicted by the fundamental law of road congestion [Duranton and Turner, 2011], much of the literature analyzing the effects of policies aimed at reducing traffic congestion find only temporary reductions. Policies analyzed include lane expansions [Duranton and Turner, 2011], expanded public transit [Gaduh et al., 2022], new road construction [He et al., 2019], and license-plate based driving restrictions [Zhang et al., 2017, Guerra et al., 2022]. We contribute to this literature by showing the ineffectiveness of another policy aimed at reducing traffic congestion, ATCS signals.

However, the installation of ATCS signals did limit the increase in traffic congestion in Los Angeles relative to the increase in the synthetic unit following the installation of the ATCS signals. The difference in annual delay at 35 mph, about two hours per resident per year, represents a substantial reduction, especially when aggregated over residents of a city the size of Los Angeles. Congestion pricing still appears to be the only effective policy for reducing traffic congestion [Tang, 2021].

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